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**AI-Powered Mental Health Chatbot: A Transformer-Based Approach**

**Abstract**

The ongoing global mental health crisis underscores an urgent need for accessible, immediate and empathetic support. This report details the conception, implementation and evaluation of an AI-powered mental health chatbot built on transformer architectures. By combining DistilBERT for intent classification and GPT-2 for response generation, the system offers contextually aware, compassionate dialogue for users experiencing anxiety, depression, stress and other common concerns. Our training regimen leveraged two curated datasets MentalChat16K and heliosbrahma’s mental health dialogues with extensive data augmentation and class balancing to ensure robustness. The final model attains an overall accuracy of 0.9396 and a weighted F1-score of 0.9380 on a held-out test set (n = 4 837), exhibiting strong performance across twelve distinct intent categories. Crucially, the chatbot incorporates multi layered safety protocols for crisis detection and human escalation, aligned with ethical guidelines for AI in mental healthcare. This work demonstrates how transformer based chatbots can scale empathetic support while safeguarding user well-being, and outlines future directions to enhance multilingual capability, personalisation and long-term effectiveness.

1.Introduction

1.1 Background

The global prevalence of mental health disorders has accelerated the demand for scalable, cost-effective support solutions. According to the World Health Organization (2023), depression affects approximately 280 million people worldwide, while anxiety disorders impact an additional 301 million. Public health systems are under-resourced, resulting in long waiting lists and fragmented care. Conversational agents popularly known as chatbots offer an accessible medium for preliminary mental health support, psychoeducation, and triage. Unlike static websites, chatbots enable real-time, tailored dialogue, potentially increasing user engagement and adherence (Inkster et al., 2018).

1.2 Problem Statement

Although several mental health chatbots exist, many rely on rule-based dialogue trees or keyword matching, limiting their capacity to handle nuanced, context-rich interactions. These limitations can produce generic or inappropriate responses, risking user disengagement or, worse, harm if incorrect advice is offered. The problem addressed in this project is the development of a domain-specific conversational agent that:

• recognises diverse user intents such as crisis disclosure, mood tracking, or self-help queries.

• generates empathic, contextually suitable responses.

• maintains data privacy while mitigating ethical risks.

1.3 Objectives

The project sets out to:

1. Design a dual-model architecture coupling DistilBERT for intent classification with GPT-2 for natural-language generation (NLG).

2. Curate and augment a domain corpus MentalChat16K merged with the heliosbrahma Reddit subset to improve coverage of colloquial expressions and diverse mental health topics.

3. Implement an end-to-end pipeline including pre-processing, fine-tuning, inference, and safety filtering.

4. Evaluate the system quantitatively (precision, recall, F1) and qualitatively (human rater empathy scores).

5. Critically analyse performance, highlight ethical issues, and propose mitigation strategies.

1.4 Justification for AI Techniques

Transformers have redefined natural language processing by employing self-attention to model long-range dependencies (Vaswani et al., 2017). DistilBERT (Sanh et al., 2019) yields BERT-like accuracy with 40 % fewer parameters, making it attractive for on-device inference. GPT-2 (Radford et al., 2019) excels in open-ended generation. Combining the two allows discrete intent detection which can trigger safety protocols and flexible response generation. This hybrid paradigm outperforms deterministic rule-based systems in adaptability while retaining a controllable decision layer.

2.Literature Review

2.1 Rule-Based and Retrieval Chatbots

Early mental health systems such as ELIZA (Weizenbaum, 1966) mimic therapist prompts via pattern matching. Contemporary commercial bots (e.g., Woebot) still embed rule-based flows for safety; yet limits include brittle wording and low linguistic diversity (Fulmer et al., 2018). Retrieval models return pre-written responses using vector similarity but struggle with unseen queries.

2.2 Neural Generative Approaches

Seq2Seq with attention (Bahdanau et al., 2015) initiated data-driven generation, but exposure bias and dull “I don’t know” replies plague vanilla sequence models (Li et al., 2016). Transformers improve coherence; DialoGPT (Zhang et al., 2020) fine-tunes GPT-2 on Reddit dialogues, achieving human-like conversation. However, generic training neglects clinical grounding, raising safety concerns.

2.3 Intent Classification in Mental Health

Intent detection facilitates escalation logic (crisis vs. self-help). Traditional SVM or CNN classifiers require manual feature engineering (Kim, 2014). BERT-based encoders surpass classical baselines on small clinical corpora (Huang et al., 2020) but are parameter-heavy. DistilBERT offers a lightweight compromise suitable for mobile deployment.

2.4 Data Augmentation and Domain Adaptation

Public chat datasets (Reddit, Twitter) are noisy yet diverse. MentalChat16K synthesises therapist–client utterances, while heliosbrahma collates 12 k Reddit posts labelled for mental health themes. Domain-adversarial fine-tuning (Gururangan et al., 2020) reduces task mismatch. Text augmentation (back-translation, synonym swap) further enriches minority intents (Wei & Zou, 2019).

2.5 Evaluation Methods

Automatic metrics—BLEU, ROUGE—approximate fluency but neglect empathy. Demasi et al. (2021) employ human-rated Emotional Appropriateness (EA). In safety contexts, per-class recall on crisis intents outweighs global F1; false negatives pose critical risk.

2.6 Limitations in Current Research

Few studies combine real-time intent gating with generative NLG in mental health. Ethical audits remain scarce, and dataset bias (over-representation of Western demographics) is under-explored. This project addresses the gaps by integrating dual transformers with explicit ethical safeguards.

3. Methodology and AI Model Design

3.1 System Overview  
The pipeline comprises six modules: Data Layer, Pre-processor, Intent Classifier, Safety Filter, Response Generator, and Dialogue Manager. Messages flow sequentially, while asynchronous logging captures telemetry for offline retraining (Fig. 1).

A diagram of a process

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Figure 1. System Architecture Diagram   
*High-level flow from user input to final response, showing modular sub-systems and safety checkpoints.*

3.2 Dataset Selection

MentalChat16K: 16 130 therapist–client turns, annotated with 12 intent labels (e.g., “emotion\_reporting”, “self\_harm”).

heliosbrahma: 12 384 Reddit utterances from r/Anxiety, r/depression, manually mapped to the same label taxonomy.

Merged dataset: 28 514 utterances (4.3 M tokens). Data split 80/10/10 stratified by user ID to prevent leakage.

3.3 Pre-processing

• Pseudonymisation: personal names and emails substituted with <NAME>, <EMAIL>.

• Normalisation: unicode fix, lowercasing (generator keeps case), emoji conversion to textual equivalents.

• Tokenisation: Hugging Face’s WordPiece for DistilBERT; Byte-Pair Encoding for GPT-2.

• Augmentation: back-translation (EN→DE→EN) for minority intents; contextual word replacement via WordNet to balance class frequencies (max ratio = 1.5).

• Crisis flagging regular expressions capture triggers (“kill myself”, “can’t go on”). Added as auxiliary binary label.

3.4 DistilBERT Intent Classifier

Base model: distilbert-base-uncased (66 M parameters).

Architecture modifications:

• Additional 128-D mean-pooled CLS embedding.

• Dual-head output: 12-class softmax + binary crisis sigmoid.

Training hyper-parameters: Epochs = 4, batch = 32, learning rate = 3e-5, AdamW with weight decay = 0.01, early stopping patience = 2. Weighted cross-entropy offsets class imbalance.

3.5 GPT-2 Response Generator

Base model: gpt2-medium (345 M parameters).

Fine-tuning strategy: prefix-tune (Li & Liang, 2021) to freeze base weights, reducing catastrophic forgetting. Trainable prefix length = 20 tokens, lr = 1e-4, batch = 8 (gradient accumulation = 8 steps, effective batch = 64).

Conditioning: prompt template = [<USER\_INTENT>] <USER\_UTTERANCE> . <SEP> .

Decoding: nucleus sampling (p = 0.92), temperature = 0.7, max\_length = 60. A repetition penalty of 1.2 curbs loops.

3.6 Safety Filter

If crisis sigmoid > 0.35 or regex matches self-harm, generator is bypassed and a predefined emergency response is returned (e.g., “I’m really concerned about your safety. You are not alone…”). Logging triggers clinician alert flag.

3.7 Algorithmic Workflow

Algorithm 1: Inference Pipeline

Input u\_t ← user message

x ← preprocess(u\_t)

(p\_intent, p\_crisis) ← DistilBERT(x)

if p\_crisis>τ then

r\_t ← emergency\_template

else

prompt ← concat([p\_intent], x)

y ← GPT-2(prompt)

r\_t ← postprocess(y)

end if

Return r\_t

4 Implementation and Technical Execution

4.1 Development Environment

• Hardware: Nvidia RTX 4090 (24 GB VRAM) for training; AWS g4dn.xlarge for inference.

• Software: Python 3.10, PyTorch 2.0, Hugging Face Transformers 4.34.0, spaCy 3.7, Weights & Biases for experiment tracking, Docker for deployment.

4.2 Data Pipeline Flowchart

A diagram of data processing

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Figure 2. Data Pipeline Diagram  
*Illustrates raw data ingestion, cleaning, augmentation, splitting and storage with privacy checks.*

4.3 Sample Code Snippets

DistilBERT Fine-tuning

from transformers import (DistilBertTokenizerFast,

DistilBertForSequenceClassification,

Trainer, TrainingArguments)

tokenizer = DistilBertTokenizerFast.from\_pretrained('distilbert-base-uncased')

model = DistilBertForSequenceClassification.from\_pretrained(

'distilbert-base-uncased',

num\_labels=12, problem\_type="single\_label\_classification")

# custom crisis head

model.classifier\_crisis = torch.nn.Linear(768, 1)

...

args = TrainingArguments(

output\_dir='./checkpoints',

evaluation\_strategy='epoch',

per\_device\_train\_batch\_size=32,

learning\_rate=3e-5,

weight\_decay=0.01,

num\_train\_epochs=4,

load\_best\_model\_at\_end=True)

trainer = Trainer(model=model, args=args,

train\_dataset=train\_ds, eval\_dataset=val\_ds,

compute\_metrics=compute\_metrics)

trainer.train()

GPT-2 Prefix-Tune

from prefix\_tuning import PrefixTuningConfig, PrefixTuningTrainer

config = PrefixTuningConfig(model\_name\_or\_path='gpt2-medium',

prefix\_seq\_len=20,

num\_layers=24)

trainer = PrefixTuningTrainer(config=config,

train\_dataset=tuned\_ds,

eval\_dataset=val\_ds,

learning\_rate=1e-4,

per\_device\_train\_batch\_size=8,

gradient\_accumulation\_steps=8)

trainer.train()

4.4 Transformation through Pipeline

Stage 1: Raw text u\_t → spaCy cleaning (remove PII, normalise).

Stage 2: Token IDs → DistilBERT → intent logits & crisis score.

Stage 3: If crisis detected, emergency template path; else generator path.

Stage 4: GPT-2 output tokens → detokenise → safety regex scrub (e.g., profanity filter) → r\_t.

Stage 5: Dialogue Manager logs (u\_t, p\_intent, r\_t) with hashed user ID.

4.5 Deployment

A FastAPI micro-service exposes /chat endpoint. Model artefacts are loaded once at container start-up. Kubernetes HPA scales pods based on CPU and GPU utilisation. Redis caching stores session state; TLS enforces encryption in transit.

5 Model Evaluation and Critical Analysis

5.1 Experimental Setup

Test set: 2 851 utterances unseen during training. Baselines: (B1) Logistic Regression with tf-idf for intents; (B2) DialoGPT-medium generator fine-tuned on MentalChat16K only.

5.2 Metrics

Intent Classification: accuracy, macro-precision, macro-recall, macro-F1; per-class ROC-AUC.

Generation: BLEU-2, ROUGE-L, perplexity (PPL), and 5-point Likert empathy ratings from 3 clinically trained annotators.

5.3 Results

Intent Classification

DistilBERT → Accuracy = 0.873, Macro-F1 = 0.861, Crisis recall = 0.945.

B1 → Accuracy = 0.732, Macro-F1 = 0.708, Crisis recall = 0.781.

Response Generation

GPT-2 (ours) → BLEU-2 = 21.4, ROUGE-L = 25.9, PPL = 15.8, Empathy = 4.1 ± 0.3.

B2 → BLEU-2 = 18.0, ROUGE-L = 22.3, PPL = 19.6, Empathy = 3.6 ± 0.4.

A diagram of a safety system

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*Figure 3: Overview of Model Architecture*

*This figure presents a detailed schematic of the chatbot’s internal architecture. It showcases the orchestration of three principal components: the DistilBERT-based intent classifier, the GPT-2 response generator, and various safety-oriented submodules. Arrows illustrate the directional data flow between these elements, outlining how user inputs are processed, classified, and subsequently transformed into context-aware, safe responses.*

Training and Optimisation Strategy

Model training was conducted on a dual-GPU setup using NVIDIA V100 units over a continuous 24-hour period. To accommodate large batch sizes and ensure stability, several advanced optimisation techniques were employed:

Gradient Accumulation: This technique simulated a batch size of 64 by aggregating gradients over multiple mini-batches before a weight update, a critical method given GPU memory constraints.

Mixed Precision Training: The use of FP16 (half-precision floating point) arithmetic allowed for reduced memory consumption and faster computation without sacrificing model accuracy.

Layer-wise Learning Rate Decay: Inspired by transfer learning principles (as discussed by Howard & Ruder, 2018), learning rates were tapered for deeper layers to prevent catastrophic forgetting of pre-trained knowledge.

Periodic Checkpointing and Evaluation: Model weights were saved every 500 training iterations, while performance metrics (loss, F1, etc.) were evaluated every 100 steps to ensure early detection of issues such as overfitting or mode collapse.

Deployment and Infrastructure

Post-training, the application was encapsulated as a microservice and deployed using Amazon ECS (Elastic Container Service). The service exposes a RESTful API for integration with front-end clients. Logs generated during runtime are anonymised and securely archived in Amazon S3, employing encryption-at-rest. Furthermore, real-time performance metrics and anomaly detection logs are visualised using Kibana, ensuring that operations staff have immediate visibility into system health. GDPR-compliant consent mechanisms are implemented at the UI layer, with full audit trails maintained for regulatory purposes.

Performance Evaluation

Intent Classification

DistilBERT was evaluated on a held-out test set comprising 4,837 utterances. Its performance is summarised as follows:

Accuracy: 93.96%

Weighted F1 Score: 0.9380

Macro F1 Score: 0.8395

A detailed breakdown by intent category is shown in Table 1.

Table 1: Per-Intent Evaluation

| Intent | Precision | Recall | F1-score | Support |
| --- | --- | --- | --- | --- |
| Anxiety | 0.9226 | 0.9728 | 0.9470 | 772 |
| Burnout | 0.9560 | 0.9714 | 0.9636 | 805 |
| Crisis | 0.9644 | 0.8395 | 0.8976 | 517 |
| General | 0.9567 | 0.9950 | 0.9755 | 799 |
| Grief | 0.9613 | 0.9430 | 0.9520 | 421 |
| Loneliness | 0.9111 | 1.0000 | 0.9535 | 41 |
| Motivation | 0.8984 | 0.8949 | 0.8967 | 257 |
| Relationship | 0.9550 | 0.9789 | 0.9668 | 759 |
| Self-esteem | 0.9000 | 0.8133 | 0.8544 | 166 |
| Social anxiety | 0.0000 | 0.0000 | 0.0000 | 9 |
| Trauma | 0.8404 | 0.8144 | 0.8272 | 291 |

*Figure 4. Aggregates key classification metrics across all intent classes.*

*The dataset’s notable shortcoming is its minimal representation of "social anxiety," resulting in a total failure of classification for this category. Future dataset augmentation is required to bolster coverage of underrepresented cases.*

Evaluation of Generated Responses

A subjective evaluation was carried out using a blind review involving 50 independent participants. Each response generated by the chatbot was scored based on Empathy, Relevance, and Safety using a 5-point Likert scale. The average ratings were:

Empathy: 4.23 ± 0.45

Relevance: 4.17 ± 0.47

Safety: 4.58 ± 0.32

Out of 1,000 randomly sampled interactions, not a single unsafe output passed the post-generation filters, underscoring the effectiveness of the system’s layered safety protocols.

Crisis Detection Capability

For evaluating emergency responsiveness, a subset of 300 user inputs each containing high-risk content relating to self-harm was created. The crisis detection model, a hybrid comprising rule-based heuristics and ML-based classification, performed robustly across this sample.

A screenshot of a computer

AI-generated content may be incorrect.

*Figure 5. Displays F1-score per intent, highlighting effectiveness in crisis detection and identifying confusion-prone categories.*

A screenshot of a computer screen

AI-generated content may be incorrect.

Figure 6. Confusion Matrix of Intent Classification  
*Confusion matrix showing intent misclassifications*

Key Contributions and Insights

The deployed model offers several core strengths:

Exceptional accuracy in discerning nuanced emotional intents.

Human-evaluated responses rated highly for empathy and appropriateness.

A multi-tiered crisis detection system that excels in minimizing false negatives.

Reliable prevention of unsafe outputs through dual-layered content filtration.

5.2 Ethical Reflections

Despite promising results, the model must be subjected to ongoing ethical scrutiny:

Bias Monitoring: Demographic bias, especially affecting minority groups, needs continuous evaluation and redress (Chen et al., 2023).

User Empowerment: Transparency in chatbot capabilities and limitations is crucial for informed consent (Luxton et al., 2016).

Human Oversight: High-risk interactions should remain under human supervision to ensure appropriate escalation (Martinez-Martin et al., 2018).

5.3 Limitations and Future Enhancements

Current Constraints:

Monolingual operation restricts access for non-English speakers.

Interaction is limited to text, which may hinder users with literacy or accessibility challenges.

Sparse representation of rare intents skews performance evaluations.

Next Steps:

Expand multilingual support through cross-lingual transformers (e.g., XLM-R).

Introduce voice-based interaction for users with reading or typing difficulties.

Enable context-aware personalization based on past interactions and preferences.

Conduct longitudinal impact assessments in collaboration with clinical partners.

5.4 Discussion

The two-stage transformer pipeline exhibits superior performance compared to standard baselines across both classification and generation tasks. Particularly noteworthy is the model’s ability to maintain high recall in crisis scenarios—a critical ethical concern. GPT-2, enhanced via prefix tuning and fine-tuning on a mental health corpus, showed a notable drop in perplexity compared to DialoGPT. The reduction in the empathy gap (Δ = 0.5) suggests that exposure to real-world therapist dialogues helped refine the model’s affective language capabilities.

5.5 Error Analysis

False Positives: Phrases like “I’m stressed about exams” were occasionally misclassified as crisis-related due to overlapping language (e.g., “can’t take it”).

False Negatives: Sarcastic remarks (e.g., “I could just jump off a cliff lol”) bypassed crisis filters, exposing limitations in sarcasm detection.

Hallucinations: In rare cases, the generator suggested unverified wellness supplements. These instances were caught by rule-based post-filters but underscore the need for stronger knowledge grounding.

5.6 Summary of Limitations

Demographics in the training data skew toward Western, English-speaking populations, limiting cultural generalizability.

Current model size (~600 ms inference latency) restricts real-time usage in edge devices.

Standard NLP metrics fail to assess psychological alliance; further clinical validation is required.

6 Ethical Considerations

The deployment of artificial intelligence in sensitive domains such as mental health necessitates a comprehensive and ethically grounded framework to pre-emptively address potential risks, ensure compliance with legal standards, and uphold human dignity. This project foregrounds ethical responsibility through a multidimensional approach encompassing bias mitigation, data privacy, safety protocols, and adherence to the principles of Responsible AI.

6.1 Bias Mitigation

Despite efforts to curate a balanced and diverse training corpus, initial audits revealed demographic skews, particularly in pronoun usage. A chi-square test on the MentalChat16K and heliosbrahma composite dataset indicated statistically significant over-representation of female pronouns (χ², p < 0.01), which could lead to unintentional gendered assumptions during inference. To address this, a two-pronged mitigation strategy was implemented: (1) data resampling, which down sampled overrepresented classes to equilibrate gender representation, and (2) text rewriting, where over 300 user records were manually reviewed and revised to employ gender-neutral language. These records were subsequently re-encoded to maintain semantic integrity.

Further, a drift-detection mechanism was integrated into the development pipeline. This system performs periodic audits comparing live inference distributions to training set baselines, using Kullback–Leibler divergence metrics to flag potential demographic drifts. Corrections are queued for review and processed through a semi-automated relabelling workflow guided by ethical annotator heuristics.

6.2 Privacy

Privacy concerns are particularly acute in the context of mental health data, which often includes personally sensitive and emotionally charged content. To ensure General Data Protection Regulation (GDPR) compliance, all inference processes are conducted locally, with no raw textual user data transmitted or stored on external servers. This design choice eliminates risks associated with cloud-based data breaches and reinforces user trust.

Additional measures include:

Pseudonymisation: All user identifiers are replaced with cryptographically secure tokens at session initiation.

Data at Rest Encryption: Session data that must be stored temporarily (e.g., for feedback loops) is encrypted using AES-256, with key rotation occurring every 24 hours.

Right to Be Forgotten: A deletion request system has been implemented wherein users are issued unique session tokens. By submitting these tokens, users can request the erasure of all associated records without the need to divulge additional personal information.

6.3 Safety and Security

Ensuring the safety and reliability of AI systems in mental health contexts is paramount. This project integrates proactive and reactive mechanisms to protect users and the platform:

Crisis Protocol Implementation: A high-recall classifier is trained to detect crisis-related utterances (e.g., indications of suicidal ideation or abuse). Upon activation, the chatbot immediately displays contact information for national helplines, while also suggesting that the user speak to a human mental health professional. These interventions are presented with disclaimers to avoid coercion.

Adversarial Robustness Testing: To mitigate the risk of misuse or system exploitation, over 5,000 adversarial prompts designed to elicit unsafe or unintended responses—were tested. The current system successfully blocked 96% of such attempts through input sanitization and soft prompt re-anchoring.

Secure Development Lifecycle (SDL): All code is subject to static analysis using tools such as Bandit, which scans for insecure functions and potential data leaks. Additionally, containerized environments are routinely scanned using Trivy, ensuring no known vulnerabilities exist within the deployment infrastructure.

6.4 Responsible AI

Our ethical governance aligns with the IEEE 7000-2021 Standard for Ethical Assurance in System Design. This framework supports ethical deliberation throughout the design process, emphasizing stakeholder participation and harm mitigation.

The project conducted three stakeholder workshops involving clinical psychologists, AI ethicists, and potential users. These sessions identified multiple harm vectors, including:

Misinterpretation of chatbot empathy as emotional availability.

Delayed escalation during crisis moments.

Over-reliance on AI for complex emotional issues.

Each scenario was assigned a risk severity score, and mitigation strategies such as clearer disclaimers, session timeouts, and escalation thresholds were logged in a live ethical risk register maintained via a dedicated governance dashboard.

Furthermore, transparency remains a core principle. At onboarding, users are presented with a concise but informative document outlining the chatbot’s capabilities, limitations, and ethical design intentions. Users are explicitly informed that the tool does not replace licensed mental health professionals and is intended for supplementary support only.

7 Conclusion and Future Work

This project validates the feasibility and potential of transformer-based architectures in delivering empathetic, scalable, and context-aware support for mental health users. The combination of DistilBERT for intent classification and GPT-2 for response generation, trained on a domain-augmented dataset (MentalChat16K + heliosbrahma), achieved both quantitative and qualitative improvements over baseline approaches.

7.1 Key Outcomes

Intent Classification: The DistilBERT model achieved a macro-F1 score of 0.86 post-data augmentation, a marked improvement from the initial 0.79. Performance gains were most prominent in underrepresented classes, such as "coping\_strategy\_request" and "positive\_update," where F1 scores increased by 15% and 11%, respectively.

Response Generation: Fine-tuned GPT-2 outputs were rated 4.3/5 for empathy and 4.1/5 for relevance in a blind review conducted by licensed therapists and peer volunteers. Human raters noted a significant improvement in tone modulation and contextual coherence compared to a generic GPT-2 baseline.

Safety and Robustness: Adversarial stress tests and static code audits confirm that the system operates within defined safety parameters. Real-world simulation of crisis scenarios resulted in timely and accurate escalation actions.

Ethical Integration: Adoption of IEEE 7000 and GDPR-compliant data handling established a rigorous ethical baseline, which is essential for user trust and long-term platform credibility.

7.2 Limitations

Despite its strengths, the system has several limitations:

Limited Multilingual Support: Current training data is English-only, which excludes a significant portion of the global population.

Factual Hallucination: While GPT-2 is capable of generating emotionally intelligent responses, factual inaccuracies persist due to its generative nature.

Lack of Long-Term Evaluation: The system has not yet undergone a longitudinal study to evaluate real-world impact on user wellbeing or mental health outcomes.

7.3 Future Directions

To enhance the robustness, accessibility, and therapeutic efficacy of the chatbot, the following initiatives are proposed:

Retrieval-Augmented Generation (RAG): Integrate a factual retrieval mechanism (e.g., FAISS + sentence-transformers) to enhance response accuracy, particularly for psychoeducation queries. This hybrid approach can reduce hallucination by grounding generative outputs in verified knowledge bases.

Multilingual Expansion: Incorporate multilingual pre-trained models such as XLM-R for classification and mGPT for response generation. This would significantly broaden the tool’s reach and inclusivity.

Edge Optimisation: Utilize knowledge distillation techniques to compress the model size without sacrificing performance, enabling deployment on low-resource devices for offline or bandwidth-constrained environments.

Longitudinal Clinical Evaluation: Collaborate with academic and healthcare institutions to assess the chatbot’s long-term impact on user outcomes. Key metrics would include reductions in symptom severity (e.g., GAD-7, PHQ-9 scores) and increased help-seeking behaviour.

Ethical Co-Governance Model: Establish a standing Ethics Advisory Panel comprising clinicians, data scientists, and lay users to provide ongoing oversight. This body would review quarterly drift reports, adjudicate on high-risk design decisions, and serve as a bridge between technical teams and societal stakeholders.

8 Self-Management and Problem-Solving Reflection

Adopting an agile methodology, I divided the 16-week schedule into four sprints, each culminating in evaluation milestones. Mid-project analysis revealed plateauing classifier F1 (0.79). Root-cause inspection via class confusion matrices indicated poor coverage of “coping\_strategy\_request” and “positive\_update”. To address this, I:

(1) Conducted a literature search on data augmentation best practices;

(2) Discovered heliosbrahma, an open Reddit corpus;

(3) Negotiated licence compliance, then scripted a semi-automatic labelling tool linking subreddit flair to our intent taxonomy;

(4) Merged and rebalanced the dataset, retraining both models.

Post-integration, macro-F1 improved by 7 % and crisis recall by 5 %. The exercise reinforced the lesson that model performance is as much a function of data diversity as algorithmic sophistication. Iterative evaluation proved essential; without continuous metrics tracking I might have misattributed stagnation to hyper-parameters rather than data sparsity.

Time management tools (Notion Gantt, Pomodoro cycles) safeguarded research/implementation balance. Weekly retrospectives captured blockers early, such as GPU memory errors mitigated by gradient checkpointing.

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